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**Please find below and/or attached an Office communication concerning this application or proceeding.**

The time period for reply, if any, is set in the attached communication.

| Office Action Summary | Application No. 10/658,623 | Applicant(s) FAN, WEI | |
|---|---|---|---|
| | Examiner Wilbert L. Starks, Jr. | Art Unit 2129 | |

*-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --*

**Period for Reply**

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE 3 MONTH(S) OR THIRTY (30) DAYS, WHICHEVER IS LONGER, FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

**Status**

1)☒ Responsive to communication(s) filed on 24 May 2007.

2a)☐ This action is **FINAL**. 2b)☒ This action is non-final.

3)☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

**Disposition of Claims**

4)☒ Claim(s) 1-26 is/are pending in the application.

4a) Of the above claim(s) _____ is/are withdrawn from consideration.

5)☐ Claim(s) _____ is/are allowed.

6)☒ Claim(s) 1-26 is/are rejected.

7)☐ Claim(s) _____ is/are objected to.

8)☐ Claim(s) _____ are subject to restriction and/or election requirement.

**Application Papers**

9)☐ The specification is objected to by the Examiner.

10)☐ The drawing(s) filed on _____ is/are: a)☐ accepted or b)☐ objected to by the Examiner.

Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

11)☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

**Priority under 35 U.S.C. § 119**

12)☐ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

a)☐ All b)☐ Some * c)☐ None of:

1.☐ Certified copies of the priority documents have been received.

2.☐ Certified copies of the priority documents have been received in Application No. _____.

3.☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

**Attachment(s)**

1) ☒ Notice of References Cited (PTO-892)

2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)

3) ☐ Information Disclosure Statement(s) (PTO/SB/08) Paper No(s)/Mail Date _____.

4) ☐ Interview Summary (PTO-413) Paper No(s)/Mail Date. _____.

5) ☐ Notice of Informal Patent Application

6) ☐ Other: _____.

## DETAILED ACTION

### *Claim Rejections - 35 U.S.C. §101*

1. 35 U.S.C. §101 reads as follows:

> Whoever invents or discovers any new and useful process, machine, manufacture, or composition of matter, or any new and useful improvement thereof, may obtain a patent therefor, subject to the conditions and requirements of this title.

the invention as disclosed in claims 1-26 is directed to non-statutory subject matter.

2. None of the claims is limited to practical applications that indicate a specific practical utility for the claimed invention. Examiner finds that *In re Warmerdam*, 33 F.3d 1354, 31 USPQ2d 1754 (Fed. Cir. 1994) controls the 35 U.S.C. §101 issues on that point for reasons made clear by the Federal Circuit in *AT&T Corp. v. Excel Communications, Inc.*, 50 USPQ2d 1447 (Fed. Cir. 1999). Specifically, the Federal Circuit held that the act of:

> ...[T]aking several abstract ideas and manipulating them together adds nothing to the basic equation. *AT&T v. Excel* at 1453 quoting *In re Warmerdam*, 33 F.3d 1354, 1360 (Fed. Cir. 1994).

Examiner finds that Applicant's "history files" references are just such abstract ideas.

3. Examiner bases his position upon guidance provided by the Federal Circuit in *In re Warmerdam*, as interpreted by *AT&T v. Excel*. This set of precedents is within the same line of cases as the *Alappat-State Street Bank* decisions and is in complete

agreement with those decisions. *Warmerdam* is consistent with *State Street*'s holding that:

> Today we hold that *the transformation of data, representing discrete dollar amounts, by a machine through a series of mathematical calculations into a final share price*, constitutes a practical application of a mathematical algorithm, formula, or calculation because it produces 'a useful, concrete and tangible result" -- *a final share price momentarily fixed for recording purposes and even accepted and relied upon by regulatory authorities and in subsequent trades*. (emphasis added) *State Street Bank* at 1601.

4. True enough, that case later eliminated the "business method exception" in order to show that business methods were not per se nonstatutory, but the court clearly *did not* go so far as to make business methods *per se statutory*. A plain reading of the excerpt above shows that the Court was *very specific* in its definition of the new *practical application* that indicates a specific practical utility for the claimed invention. It would have been much easier for the court to say that "business methods were per se statutory" than it was to define the practical application in the case as "...the transformation of data, representing discrete dollar amounts, by a machine through a series of mathematical calculations into a final share price..."

5. The court was being very specific.

6. Additionally, the court was also careful to specify that the "useful, concrete and tangible result" it found was "a final share price momentarily fixed for recording purposes and even accepted and relied upon by regulatory authorities and in subsequent trades." (i.e. the trading activity is the further practical use of the real world

<u>monetary</u> data beyond the transformation in the computer – i.e., "post-processing activity".)

7. Applicant cites no such specific results to define a useful, concrete and tangible result. Neither does Applicant specify the associated practical application with the kind of specificity the Federal Circuit used.

8. Furthermore, in the case *In re Warmerdam*, the Federal Circuit held that:

> ...<u>[T]he dispositive issue</u> for assessing compliance with Section 101 in this case is whether the claim is for a process that goes beyond simply <u>manipulating 'abstract ideas'</u> or 'natural phenomena' ... As the Supreme Court has made clear, '[a]n idea of itself is not patentable, ... <u>*taking several abstract ideas and manipulating them together adds nothing to the basic equation*</u>. In re Warmerdam 31 USPQ2d at 1759 (emphasis added).

9. Since the Federal Circuit held in *Warmerdam* that this is <u>the</u> "dispositive issue" when it judged the usefulness, concreteness, and tangibility of the claim limitations in that case, Examiner in the present case views this holding as the dispositive issue for determining whether a claim is "useful, concrete, and tangible" in similar cases. Accordingly, the Examiner finds that Applicant manipulated a set of abstract "history files" to solve purely algorithmic problems in the abstract (i.e., what *kind* of "history files" are used? Heart rhythm data? Algebraic equations? Boolean logic problems? Fuzzy logic algorithms? Probabilistic word problems? Philosophical ideas? Even vague expressions, about which even reasonable persons could differ as to their meaning? Combinations thereof?) Clearly, a claim for manipulation of "history files" is provably even more abstract (and thereby less limited in practical application) than pure "mathematical algorithms" which the Supreme Court has held are <u>per se</u> nonstatutory – in fact, it *includes* the expression of nonstatutory mathematical algorithms.

10. Since the claims are not limited to <u>exclude</u> such abstractions, the broadest reasonable interpretation of the claim limitations <u>includes</u> such abstractions. Therefore, the claims are impermissibly abstract under 35 U.S.C. §101 doctrine.

11. Since *Warmerdam* is within the *Alappat-State Street Bank* line of cases, it takes the same view of "useful, concrete, and tangible" the Federal Circuit applied in *State Street Bank*. Therefore, under *State Street Bank*, this could not be a "useful, concrete and tangible result". There is only manipulation of abstract ideas.

12. The Federal Circuit validated the use of *Warmerdam* in its more recent *AT&T Corp. v. Excel Communications, Inc.* decision. The Court reminded us that:

> Finally, **the decision in In re Warmerdam**, 33 F.3d 1354, 31 USPQ2d 1754 (Fed. Cir. 1994) **is not to the contrary**. *** The court found that the claimed process did nothing more than manipulate basic mathematical constructs and concluded that **'taking several abstract ideas and manipulating them together adds nothing to the basic equation'**; hence, the court held that the claims were properly rejected under §101 ... Whether one agrees with the court's conclusion on the facts, the **holding** of the case is a straightforward application of the basic principle that mere laws of nature, natural phenomena, and abstract ideas are not within the categories of inventions or discoveries that may be patented under §101. (emphasis added) AT&T Corp. v. Excel Communications, Inc., 50 USPQ2d 1447, 1453 (Fed. Cir. 1999).

13. Remember that in *In re Warmerdam*, the Court said that this was the dispositive issue to be considered. In the *AT&T* decision cited above, the Court reaffirms that this is the issue for assessing the "useful, concrete, and tangible" nature of a set of claims under §101 doctrine. Accordingly, Examiner views the *Warmerdam* holding as the dispositive issue in this analogous case.

14. The fact that the invention is merely the manipulation of *abstract ideas* is clear. The data referred to by Applicant's idea of "history files" is simply an abstract construct that does not provide limitations in the claims to the transformation of real world data (such as monetary data or heart rhythm data) by some disclosed process. Consequently, the necessary conclusion under *AT&T, State Street* and *Warmerdam,* is straightforward and clear. The claims take several abstract ideas (i.e., "history files" in the abstract) and manipulate them together adding nothing to the basic equation. Claims 1-26 are, thereby, rejected under 35 U.S.C. §101.

### ***Claim Rejections - 35 U.S.C. §112***

The following is a quotation of the first paragraph of 35 U.S.C. §112:

> The specification shall contain a written description of the invention, and of the manner and process of making and using it, in such full, clear, concise, and exact terms as to enable any person skilled in the art to which it pertains, or with which it is most nearly connected, to make and use the same and shall set forth the best mode contemplated by the inventor of carrying out his invention.

Claims 1-26 are rejected under 35 U.S.C. §112, first paragraph because current case law (and accordingly, the MPEP) require such a rejection if a §101 rejection is given because when Applicant has not in fact disclosed the practical application for the invention, as a matter of law there is no way Applicant could have disclosed *how* to practice the *undisclosed* practical application. This is how the MPEP puts it:

> ("The how to use prong of section 112 **incorporates as a matter of law** the requirement of 35 U.S.C. §101 that the specification disclose as a matter of fact a practical utility for the invention.... <u>If the application fails as a matter of fact to satisfy 35 U.S.C. §101, then the application **also fails as a matter of law** to enable one of ordinary skill in the art to use the invention under 35 U.S.C. §112.</u>"); In re Kirk, 376 F.2d 936, 942, 153 USPQ 48, 53 (CCPA 1967) ("Necessarily, compliance with §112 requires a description of how to use presently useful inventions, **otherwise an applicant would anomalously be required to teach how to use a useless invention.**") See, MPEP 2107.01(IV), quoting In re Kirk (emphasis added).

Examiner made a §101 utility rejection of the claims because they fail to indicate a specific practical utility (i.e., practical application) for the claimed invention. Therefore, claims 1-26 are rejected on this basis.

### ***Claim Rejections - 35 USC § 102***

1. The following is a quotation of the appropriate paragraphs of 35 U.S.C. 102 that form the basis for the rejections under this section made in this Office action:

A person shall be entitled to a patent unless –

(e) the invention was described in (1) an application for patent, published under section 122(b), by another filed in the United States before the invention by the applicant for patent or (2) a patent granted on an application for patent by another filed in the United States before the invention by the applicant for patent, except that an international application filed under the treaty defined in section 351(a) shall have the effects for purposes of this subsection of an application filed in the United States only if the international application designated the United States and was published under Article 21(2) of such treaty in the English language.

2. Claims 1-26 are rejected under 35 U.S.C. 102(e) as being anticipated by Klein (U.S. Patent Number 7,027,953; dated 11 APR 2006; class 702; subclass 184). Specifically:

## **Claim 1**

Claim 1's "recording features of normal system operations in a history file;" is anticipated by Klein, column 23, lines 54-64, where it recites:

> The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the **training set**. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

Claim 1's "automatically creating a model for each of said features of said normal system operations in said history file;" is anticipated by Klein, column 23, lines 54-64, where it recites:

> The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the **training**

> **set**. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. **After the retraining of the system, sets of new parameters for the decision process algorithms are obtained**. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

Claim 1's "calculating anomaly scores of said features of said normal system operations and storing said anomaly scores in a trained file;" is anticipated by Klein, column 2, lines 65-67 and column 3, lines 1-8, where it recites:

\

> Every fault type of a monitored component is associated with at least one pointer, defining a frequency region of a vibrational signature in a particular domain. At each pointer, the current vibrational pattern of the component, within the observed frequency region, are compared with a baseline pattern, using preferably up to nine mathematical operators referred to as "**diagnostic indices**." The set of values provided by each index when the pointer value is entered into the index is referred to herein as a vibration feature. The index is a function that provides a result by reference to a deviation from an expected "normal."

Claim 1's "establishing a threshold to evaluate whether events in live system operations are anomalies as compared to said normal system operations features are abnormal;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domains at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a **threshold level**.

Claim 1's "automatically identifying anomalous events in said live system operations based on said anomaly scores and on said threshold;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the **likelihood that the bearing outer race is failing**. In one embodiment, this indication is by observing that the aggregate index result exceeds a **threshold level**.

Claim 1's "reporting said anomalous events; and" is anticipated by Klein, column 17, lines 62-67 and column 18, lines 1-5, where it recites:

> Another operation of the diagnostic sequence is verification of over limits. A verified **over limit** results in an **alert**. The system of the present invention preferably provides the following data to assist the engine expert in analyzing the over limit event and determine its criticality: a record of all parameters before, during, and after the over limit event; relevant diagnostics history of the engine; and supporting information such as the engine maintenance schedule. The diagnostic process also detects aircraft sensor failures, which are characterized by simultaneous trend shifts of a specific parameter in all of the aircraft's engines.

Claim 1's "periodically repeating said calculating." is anticipated by Klein, column 17, lines 29-41, where it recites:

> The second stage is the Feature extraction, i.e. numerical representation of the monitored parameters characteristics. The features can be

> parameter deviations from the initialization point (snapshot), or shift of each parameter **over a number of cycles**. The basic features in current use are: snapshot, short-term shifts, long-term shifts, and varying-term shifts. It should be noted that different features provide different information about the engine. For example: snapshot and short-term shifts provide information on abrupt changes, as broken valves and open bleeds. Long-term shift are more appropriate for detection of slow deterioration of engines.

## Claim 2

Claim 2's "establishing relationships that exist between each of said features of said normal system operations;" is anticipated by Klein, column 23, lines 54-64, where it recites:

> The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the **training set**. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. **After the retraining of the system, sets of new parameters for the decision process algorithms are obtained**. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

Claim 2's "selecting a labeled feature from said features;" is anticipated by Klein, column 18, lines 6-19, where it recites:

> Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which **partitions the parameters' multidimensional space into groups**. Any unknown fault that is reflected in the snapshot data will be **classified as Novelty** until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting, multi classification methods and finally decision processes that

> <u>determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results</u>.

Claim 2's "mathematically rearranging said relationships from the point of view of said labeled feature to create a solution for said labeled feature, wherein said solution comprises a model for said labeled feature;" is anticipated by Klein, column 18, lines 6-19, where it recites:

> Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which **<u>partitions the parameters' multidimensional space into groups</u>**. Any unknown fault that is reflected in the snapshot data will be **<u>classified as Novelty</u>** until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from <u>features extracting, multi classification methods and finally decision processes that determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results</u>.

Claim 2's "selecting different features as said labeled feature and repeating said process of mathematically rearranging said relationships to produce solutions from the point of view of each remaining feature as models for the remaining features." is anticipated by Klein, column 18, lines 6-19, where it recites:

> Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which **<u>partitions the parameters' multidimensional space into groups</u>**. Any unknown fault that is reflected in the snapshot data will be **<u>classified as Novelty</u>** until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The

> automatic diagnostics sequence is combined from <u>features extracting, multi classification methods and finally decision processes that determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results</u>.

## <u>Claim 3</u>

Claim 3's "The method in claim 2, wherein said solution comprises a mathematical statement of what said labeled feature equals in terms of the relationships between the remaining features." is anticipated by Klein, column 23, lines 54-64, where it recites:

> The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. **<u>After the retraining of the system, sets of new parameters for the decision process algorithms are obtained</u>**. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

## <u>Claim 4</u>

Claim 4's "The method in claim 2, wherein said normal system operations comprise said features in said history file at the time said models are created." is anticipated by Klein, column 23, lines 54-64, where it recites:

> **<u>The retraining process</u>** depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the **<u>update</u>** of the

> airborne system or the ground station configuration, the system is able to **automatically identify the new defect**.

## Claim 5

Claim 5's "predicting a likelihood that said each feature will be normal when one or more of the other features are abnormal, using said model of each of said features;" is anticipated by Klein, Abstract, where it recites:

> A vibrational analysis system diagnosis the health of a mechanical system by reference to vibration signature data from multiple domains. Features are extracted from signature data by reference to pointer locations. The features provide an indication of signature deviation from a baseline signature in the observed domain. Several features applicable to a desired fault are aggregated to provide an indication of the **likelihood** that the fault has manifested in the observed mechanical system. The system may also be used for **trend analysis** of the health of the mechanical system.

Claim 5's "repeating said predicting using different presumptions about other features being normal and abnormal to produce said trained file of a plurality of anomaly scores for each of said features." is anticipated by Klein, column 23, lines 54-64, where it recites:

> **The retraining process** depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the **update** of the airborne system or the ground station configuration, the system is able to **automatically identify the new defect**.

## Claim 6

Claim 6's "The method in claim 5, wherein said trained file provides an normally score for each of said features for each of a plurality of different possible abnormalities." is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domaind at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate <u>index result exceeds a **threshold level**</u>.

## Claim 7

Claim 7's "determining values of features for a given operation of said system;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:


> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domaind at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate <u>**index** result exceeds a **threshold level**</u>.

Claim 7's "referring to said trained file to retrieve an anomaly score for each of said features of said given operation;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate <u>index result exceeds a **threshold level**</u>.

Claim 7's "comparing said anomaly score for each of said features of said given operation with said threshold to determine whether each anomaly score exceeds said threshold." is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate <u>index result exceeds a **threshold level**</u>.

**Claim 8**

Claim 8's "recording features of normal system operations in a history file;" is anticipated by Klein, column 23, lines 54-64, where it recites:

> The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the **training set**. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

Claim 8's "automatically creating a model for each of said features of said normal system operations in said history file;" is anticipated by Klein, column 23, lines 54-64, where it recites:

> **The retraining process** depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the **training set**. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

Claim 8's "calculating anomaly scores of said features of said normal system operations and storing said anomaly scores in a trained file;" is anticipated by Klein, column 2, lines 65-67 and column 3, lines 1-8, where it recites:

> Every fault type of a monitored component is associated with at least one pointer, defining a frequency region of a vibrational signature in a particular domain. At each pointer, the current vibrational pattern of the component, within the observed frequency region, are compared with a baseline pattern, using preferably up to nine mathematical operators referred to as "**diagnostic indices**." The set of values provided by each index when the pointer value is entered into the index is referred to herein as a vibration feature. The index is a function that provides a result by reference to a deviation from an expected "normal."

Claim 8's "establishing a threshold to evaluate whether events in live system operations are anomalies as compared to said normal system operations;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domaind at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a **threshold level**.

Claim 8's "automatically identifying anomalous events in said live system operations based on said anomaly scores and on said threshold; reporting said anomalous event; and " is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domaind at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the

> analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the **likelihood that the bearing outer race is failing**. In one embodiment, this indication is by observing that the aggregate index result exceeds a **threshold level**.

Claim 8's "periodically repeating said calculating; " is anticipated by Klein, column 17, lines 29-41, where it recites:

> The second stage is the Feature extraction, i.e. numerical representation of the monitored parameters characteristics. The features can be parameter deviations from the initialization point (snapshot), or shift of each parameter **over a number of cycles**. The basic features in current use are: snapshot, short-term shifts, long-term shifts, and varying-term shifts. It should be noted that different features provide different information about the engine. For example: snapshot and short-term shifts provide information on abrupt changes, as broken valves and open bleeds. Long-term shift are more appropriate for detection of slow deterioration of engines.

Claim 8's "establishing relationships that exist between each of said features for said normal system operations;" is anticipated by Klein, column 23, lines 54-64, where it recites:

> The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the **training set**. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. **After the retraining of the system, sets of new parameters for the decision process algorithms are obtained**. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

Claim 8's "selecting a labeled feature from said features; mathematically rearranging said relationships from the point of view of said labeled feature to create a solution for

said labeled feature, wherein said solution comprises a model for said labeled feature;" is anticipated by Klein, column 18, lines 6-19, where it recites:

> Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which **partitions the parameters' multidimensional space into groups**. Any unknown fault that is reflected in the snapshot data will be **classified as Novelty** until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting, multi classification methods and finally decision processes that determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results.

Claim 8's "selecting different features as said labeled feature and repeating said process of mathematically rearranging said relationships to produce solutions from the point of view of each remaining feature as models for the remaining features." is anticipated by Klein, column 18, lines 6-19, where it recites:

> Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which **partitions the parameters' multidimensional space into groups**. Any unknown fault that is reflected in the snapshot data will be **classified as Novelty** until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting, multi classification methods and finally decision processes that determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results.

## Claim 9

Claim 9's "The method in claim 8, wherein said solution comprises a mathematical statement of what said labeled feature equals in terms of the relationships between the remaining features." is anticipated by Klein, column 23, lines 54-64, where it recites:

> The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. **After the retraining of the system, sets of new parameters for the decision process algorithms are obtained**. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

## Claim 10

Claim 10's "The method in claim 8, wherein said normal system operations comprise said features in said history file at the time said models are created." is anticipated by Klein, column 23, lines 54-64, where it recites:

> **The retraining process** depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the **update** of the airborne system or the ground station configuration, the system is able to **automatically identify the new defect**.

## Claim 11

Claim 11's "predicting a likelihood that each feature will be normal when one or more of the other features are abnormal, using said model of each of said features;" is anticipated by Klein, Abstract, where it recites:

> A vibrational analysis system diagnosis the health of a mechanical system by reference to vibration signature data from multiple domains. Features are extracted from signature data by reference to pointer locations. The features provide an indication of signature deviation from a baseline signature in the observed domain. Several features applicable to a desired fault are aggregated to provide an indication of the **likelihood** that the fault has manifested in the observed mechanical system. The system may also be used for **trend analysis** of the health of the mechanical system.

Claim 11's "repeating said predicting using different presumptions about other features being normal and abnormal to produce said trained file of a plurality of anomaly scores for each of said features." is anticipated by Klein, column 23, lines 54-64, where it recites:

> **The retraining process** depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the **update** of the airborne system or the ground station configuration, the system is able to **automatically identify the new defect**.

## Claim 12

Claim 12's "The method in claim 11, wherein said trained file provides an normally score for each of said features for each of a plurality of different possible abnormalities." is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate <u>index result exceeds a **threshold level**</u>.

## <u>Claim 13</u>

Claim 13's "determining values of features for a given operation of said system;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate <u>**index** result exceeds a **threshold level**</u>.

Claim 13's "referring to said trained file to retrieve an anomaly score for each of said features of said given operation;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the

> analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a **threshold level**.

Claim 13's "comparing said anomaly score for each of said features of said given operation with said threshold to determine whether each anomaly score exceeds said threshold." is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a **threshold level**.

## Claim 14

Claim 14's "recording features of normal system operations in a history file;" is anticipated by Klein, column 23, lines 54-64, where it recites:

> The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the **training set**. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

Claim 14's "automatically creating a model for each of said features of said normal system operations in said history file;" is anticipated by Klein, column 23, lines 54-64, where it recites:

> **The retraining process** depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the **training set**. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

Claim 14's "calculating anomaly scores of said features of said normal system operations and storing said anomaly scores in a trained file;" is anticipated by Klein, column 2, lines 65-67 and column 3, lines 1-8, where it recites:

> Every fault type of a monitored component is associated with at least one pointer, defining a frequency region of a vibrational signature in a particular domain. At each pointer, the current vibrational pattern of the component, within the observed frequency region, are compared with a baseline pattern, using preferably up to nine mathematical operators referred to as "**diagnostic indices**." The set of values provided by each index when the pointer value is entered into the index is referred to herein as a vibration feature. The index is a function that provides a result by reference to a deviation from an expected "normal."

Claim 14's "establishing a threshold to evaluate whether events in live system operations are anomalies as compared to said normal system operations;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate <u>index result exceeds a **threshold level**</u>.

Claim 14's "automatically identifying anomalous events in said system operations based on said anomaly scores and on said threshold;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the <u>**likelihood that the bearing outer race is failing**</u>. <u>In one embodiment, this indication is by observing</u> that the aggregate <u>index result exceeds a **threshold level**</u>.

Claim 14's "reporting said anomalous events; and" is anticipated by Klein, column 17, lines 62-67 and column 18, lines 1-5, where it recites:

> Another operation of the diagnostic sequence is verification of over limits. <u>A verified **over limit** results in an</u> <u>**alert**</u>. The system of the present invention preferably provides the following data to assist the engine expert in analyzing the over limit event and determine its criticality: a record of all parameters before, during, and after the over limit event; relevant diagnostics history of the engine; and supporting information such as the engine maintenance schedule. The diagnostic process also detects aircraft sensor failures, which are characterized by simultaneous trend shifts of a specific parameter in all of the aircraft's engines.

Claim 14's "periodically repeating said calculating; " is anticipated by Klein, column 17, lines 29-41, where it recites:

> The second stage is the Feature extraction, i.e. numerical representation of the monitored parameters characteristics. The features can be parameter deviations from the initialization point (snapshot), or shift of each parameter **over a number of cycles**. The basic features in current use are: snapshot, short-term shifts, long-term shifts, and varying-term shifts. It should be noted that different features provide different information about the engine. For example: snapshot and short-term shifts provide information on abrupt changes, as broken valves and open bleeds. Long-term shift are more appropriate for detection of slow deterioration of engines.

Claim 14's "wherein said calculating comprises: predicting a likelihood that each feature will be normal when one or more of the other features are abnormal, using said model of each of said features;" is anticipated by Klein, Abstract, where it recites:

> A vibrational analysis system diagnosis the health of a mechanical system by reference to vibration signature data from multiple domains. Features are extracted from signature data by reference to pointer locations. The features provide an indication of signature deviation from a baseline signature in the observed domain. Several features applicable to a desired fault are aggregated to provide an indication of the **likelihood** that the fault has manifested in the observed mechanical system. The system may also be used for **trend analysis** of the health of the mechanical system.

Claim 14's "repeating said predicting using different presumptions about other features being normal and abnormal to produce said trained file of a plurality of anomaly scores for each of said features." is anticipated by Klein, column 23, lines 54-64, where it recites:

> **The retraining process** depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the **update** of the airborne system or the ground station configuration, the system is able to **automatically identify the new defect**.

## Claim 15

Claim 15's "establishing relationships that exist between each of said features for said normal system operations;" is anticipated by Klein, column 23, lines 54-64, where it recites:

> The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the **training set**. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. **After the retraining of the system, sets of new parameters for the decision process algorithms are obtained**. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

Claim 15's "selecting a labeled feature from said features; " is anticipated by Klein, column 18, lines 6-19, where it recites:

> Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which **partitions the parameters' multidimensional space into groups**. Any unknown fault that is reflected in the snapshot data will be **classified as Novelty** until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting,

> multi classification methods and finally decision processes that determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results.

Claim 15's "mathematically rearranging said relationships from the point of view of said labeled feature to create a solution for said labeled feature, wherein said solution comprises a model for said labeled feature;" is anticipated by Klein, column 18, lines 6-19, where it recites:

> Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which **partitions the parameters' multidimensional space into groups**. Any unknown fault that is reflected in the snapshot data will be **classified as Novelty** until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting, multi classification methods and finally decision processes that determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results.

Claim 15's "selecting different features as said labeled feature and repeating said process of mathematically rearranging said relationships to produce solutions from the point of view of each remaining feature as models for the remaining features." is anticipated by Klein, column 18, lines 6-19, where it recites:

> Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which **partitions the parameters' multidimensional space into groups**. Any unknown fault that is reflected in the snapshot data will be **classified as Novelty** until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the

> parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting, multi classification methods and finally decision processes that determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results.

## Claim 16

Claim 16's "The method in claim 15, wherein said solution comprises a mathematical statement of what said labeled feature equals in terms of the relationships between the remaining features." is anticipated by Klein, column 23, lines 54-64, where it recites:

> The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. **After the retraining of the system, sets of new parameters for the decision process algorithms are obtained**. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

## Claim 17

Claim 17's "The method in claim 15, wherein said normal system operations comprise said features in said history file at the time said models are created." is anticipated by Klein, column 23, lines 54-64, where it recites:

> **The retraining process** depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the **update** of the airborne system or the ground station configuration, the system is able to **automatically identify the new defect**.

**Claim 18**

Claim 18's "The method in claim 14, wherein said trained file provides a normally score for each of said features for each of a plurality of different possible abnormalities." is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate <u>index result exceeds a **threshold level**</u>.

**Claim 19**

Claim 19's "determining values of features for a given operation of said system;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate <u>**index** result exceeds a **threshold level**</u>.

Claim 19's "referring to said trained file to retrieve an anomaly score for each of said features of said given operation;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate <u>index result exceeds a **threshold level**</u>.

Claim 19's "comparing said anomaly score for each of said features of said given operation with said threshold to determine whether each anomaly score exceeds said threshold." is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate <u>index result exceeds a **threshold level**</u>.

**<u>Claim 20</u>**

Claim 20's "recording features of normal system operations in a history file;" is anticipated by Klein, column 23, lines 54-64, where it recites:

> The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the **training set**. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

Claim 20's "automatically creating a model for said each of said features of said normal system operations in said history file;" is anticipated by Klein, column 23, lines 54-64, where it recites:

> **The retraining process** depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the **training set**. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

Claim 20's "calculating anomaly scores of said features of said normal system operations and storing said anomaly scores in a file;" is anticipated by Klein, column 2, lines 65-67 and column 3, lines 1-8, where it recites:

> Every fault type of a monitored component is associated with at least one pointer, defining a frequency region of a vibrational signature in a particular domain. At each pointer, the current vibrational pattern of the component, within the observed frequency region, are compared with a

> baseline pattern, using preferably up to nine mathematical operators referred to as "**diagnostic indices**." The set of values provided by each index when the pointer value is entered into the index is referred to herein as a vibration feature. The index is a function that provides a result by reference to a deviation from an expected "normal."

Claim 20's "establishing a threshold to evaluate whether events in live system operations are anomalies as compared to said normal system operations;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a **threshold level**.

Claim 20's "automatically identifying anomalous events in said live system operations based on said anomaly scores and on said threshold; " is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the **likelihood that the bearing outer race is failing**. In one embodiment, this indication is by observing that the aggregate index result exceeds a **threshold level**.

Claim 20's "reporting said anomalous events; and " is anticipated by Klein, column 17, lines 62-67 and column 18, lines 1-5, where it recites:

> Another operation of the diagnostic sequence is verification of over limits. A verified **over limit** results in an **alert**. The system of the present invention preferably provides the following data to assist the engine expert in analyzing the over limit event and determine its criticality: a record of all parameters before, during, and after the over limit event; relevant diagnostics history of the engine; and supporting information such as the engine maintenance schedule. The diagnostic process also detects aircraft sensor failures, which are characterized by simultaneous trend shifts of a specific parameter in all of the aircraft's engines.

Claim 20's "periodically repeating said calculating." is anticipated by Klein, column 17, lines 29-41, where it recites:

> The second stage is the Feature extraction, i.e. numerical representation of the monitored parameters characteristics. The features can be parameter deviations from the initialization point (snapshot), or shift of each parameter **over a number of cycles**. The basic features in current use are: snapshot, short-term shifts, long-term shifts, and varying-term shifts. It should be noted that different features provide different information about the engine. For example: snapshot and short-term shifts provide information on abrupt changes, as broken valves and open bleeds. Long-term shift are more appropriate for detection of slow deterioration of engines.

**Claim 21**

Claim 21's "establishing relationships that exist between each of said features for said normal system operations;" is anticipated by Klein, column 23, lines 54-64, where it recites:

> The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the **training**

> **set**. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. **After the retraining of the system, sets of new parameters for the decision process algorithms are obtained**. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

Claim 21's "selecting a labeled feature from said features; " is anticipated by Klein, column 18, lines 6-19, where it recites:

> Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which **partitions the parameters' multidimensional space into groups**. Any unknown fault that is reflected in the snapshot data will be **classified as Novelty** until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting, multi classification methods and finally decision processes that determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results.

Claim 21's "mathematically rearranging said relationships from the point of view of said labeled feature to create a solution for said labeled feature, wherein said solution comprises a model for said labeled feature;" is anticipated by Klein, column 18, lines 6-19, where it recites:

> Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which **partitions the parameters' multidimensional space into groups**. Any unknown fault that is reflected in the snapshot data will be **classified as Novelty** until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting, multi classification methods and finally decision processes that

> determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results.

Claim 21's "selecting different features as said labeled feature and repeating said process of mathematically rearranging said relationships to produce solutions from the point of view of each remaining feature as models for the remaining features." is anticipated by Klein, column 18, lines 6-19, where it recites:

> Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which **partitions the parameters' multidimensional space into groups**. Any unknown fault that is reflected in the snapshot data will be **classified as Novelty** until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting, multi classification methods and finally decision processes that determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results.

## Claim 22

Claim 22's "The program storage device in claim 21, wherein said method further comprises a mathematical statement of what said labeled feature equals in terms of the relationships between the remaining features." is anticipated by Klein, column 23, lines 54-64, where it recites:

> The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. **After the retraining of the system, sets of new parameters for the decision**

> **process algorithms are obtained**. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

**Claim 23**

Claim 23's "The program storage device in claim 21, wherein said normal system operations comprise said features in said history file at the time said models are created." is anticipated by Klein, column 23, lines 54-64, where it recites:

> **The retraining process** depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the **update** of the airborne system or the ground station configuration, the system is able to **automatically identify the new defect**.

**Claim 24**

Claim 24's "predicting a likelihood that each feature will be normal when one or more of the other features are abnormal, using said model of each of said features;" is anticipated by Klein, Abstract, where it recites:

> A vibrational analysis system diagnosis the health of a mechanical system by reference to vibration signature data from multiple domains. Features are extracted from signature data by reference to pointer locations. The features provide an indication of signature deviation from a baseline signature in the observed domain. Several features applicable to a desired fault are aggregated to provide an indication of the **likelihood** that the fault has manifested in the observed mechanical system. The system may also be used for **trend analysis** of the health of the mechanical system.

Claim 24's "repeating said predicting using different presumptions about other features being normal and abnormal to produce said trained file of a plurality of anomaly scores for each of said features." is anticipated by Klein, column 23, lines 54-64, where it recites:

> <u>**The retraining process**</u> depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the <u>**update**</u> of the airborne system or the ground station configuration, the system is able to <u>**automatically identify the new defect**</u>.

## <u>Claim 25</u>

Claim 25's "The program storage device in claim 24, wherein said trained file provides an normally score for each of said features for each of a plurality of different possible abnormalities." is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate <u>index result exceeds a **threshold level**</u>.

## <u>Claim 26</u>

Claim 26's "determining values of features for a given operation of said system;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate **index** result exceeds a **threshold level**.

Claim 26's "referring to said trained file to retrieve an anomaly score for each of said features of said given operation;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

> As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a **threshold level**.

Claim 26's "comparing said anomaly score for each of said features of said given operation with said threshold to determine whether each anomaly score exceeds said threshold" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the ingine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a **threshold level**.

### *Response to Arguments*

3. Applicant's arguments filed 05/24/2007 have been fully considered but they are not persuasive. Specifically, Applicant argues:

## Argument 1

2. The Appellants' Position Regarding The Rejection of Claims 1-26 under 35 U.S.C. §101
The Appellants respectfully, but strongly, disagree with the Examiner's position that none of the claims is limited to practical applications that indicate a specific practical utility for the claimed invention.
(a) Appellants' Position Regarding Rejection Of Independent Claims 1 and 20

In rejecting independent claims 1 and 20 under 35 U.S.C. § 101 for being directed to non-statutory subject matter, the Examiner indicated that In re Warmerdam, 33 F.3d 1354, 31 USPQ2d 1754 (Fed. Cir. 1994), which held that "...Taking several abstract ideas and manipulating them together adds nothing to the basic equation", was controlling. Specifically, the Examiner determined that the claimed invention did not

have a useful, concrete and tangible result because the Appellant "manipulated a set of abstract 'history files' to solve purely algorithmic problems in the abstract". The Examiner further provided that "the fact that the invention is merely the manipulation of abstract ideas is clear. The data referred to by Applicant' s idea of "history files" is simply an abstract construct that does not provide limitations in the claims to the transformation of real world data (such as monetary data or heart rhythm data) by some disclosed process. Consequently, the necessary conclusion under AT&T, State Street and Warmerdam, is straight forward and clear. The claims take several abstract ideas (i.e., "history files" in the abstract) and manipulate them together adding nothing to the basic equation." The Appellants respectfully disagree.

Independent claims 1 and 20 each include the claim limitations of "recording features of normal system operations in a history file" and "creating a model for each of said features of said normal system operations in said history file". These limitations imply that during normal system operations features of the system are determined in some manner. The features are then recorded (e.g., as historical data) in a history file. Then, for each feature in the history file, a model is created. This aspect of the invention is explained in detail throughout the disclosure. For example, the Abstract provides that the system records actions performed as features in a history file and automatically creates a model for each feature. Paragraphs [0006] and [0023] provide that the invention begins with historical data maintained in a history file and that a model is created for each feature only from normal data in the history file. Paragraph [0020] references a dataset of N features from which N models are created. Therefore, the Appellants submit that contrary to the Examiner's finding the "history files" are not just abstract ideas, but rather contain real world data (i.e., a recording of features of normal system operations) from which models are created (i.e., a model is created for each feature of normal system operations that is recorded).

Furthermore, if, as indicated by the Examiner, the data referred to by the "history files" is simply an abstract construct that did not provide limitations in the claims to the transformation of real world data by some disclosed process, it was still incumbent upon the Examiner to determine whether the method otherwise produces a useful, concrete or tangible result. That is, it is generally understood that to establish utility under 35 U.S.C. § 101 method inventions as a whole must produce a "useful, concrete and tangible result." (see State Street, 149 F.3d at 1373-74, 47 USPQ2d at 1601-02). Additionally, AT&T Corp v. Excel Communications, Inc. 172 F.3d 1352, 1358-59, 50 USPQ2d 1447, 1452 (Fed. Cir. 1999) provides that physical transformation "is not an invariable requirement, but merely one example, of how a mathematical algorithm [or law of nature] may bring about a useful application." If the Examiner determines that there is no physical transformation, additional review is required to determine if the claim provides a useful, tangible and concrete result. The review by the Examiner should focus not on each step, but on whether the final result achieved by the claimed invention is "useful, concrete and tangible" (see AT&T 172 F.3d at 1358-5).

The Appellants submit that the results of the method embodiments disclosed are "useful." Specifically, the Appellants submit that a credible, specific, and substantial use for the method of the invention (namely identifying and reporting anomalous events that occur during system operations) is readily apparent and well-established in the independent claims themselves. That is, each of the independent claims provides for a method of automatically identifying anomalous situations that occur during system operations. The limiting features in each of the claims include, but are not limited to, the following: (1) "recording features of normal system operations in a history file;" (2) "automatically creating a model for each of said features of said normal system operations in said history file;" (3) "calculating anomaly scores of said features of said normal system operations and storing said anomaly scores in a trained file;" (4) "establishing a threshold to evaluate whether events in live system operations are anomalies as compared to said normal system operations;" (5) "automatically identifying anomalous events' in said live system operations based on said anomaly scores and on said threshold;" (6) "reporting said anomalous events';" and (7) "periodically repeating said calculating." Those skilled in the art would immediately appreciate why the invention is useful (i.e., would appreciate why it is important to be able to identify when anomalous events occur during system operations and to report out the occurrence of those anomalous events). This credible, specific, and substantial use for the method of the invention (namely identifying and reporting anomalous events that occur during live system operations) is further asserted in the disclosure at paragraph [0004]. That is, in order to achieve a goal of autonomic computing it is important that a target system be able to perform self-diagnosis. Per paragraph [0018], the claimed invention provides a general solution to conventional problems associated with self-diagnosis by providing a method that uses an additive approach to combine evidence from multiple sources (i.e., history files) and then uses a probabilitstic thresholding approach to detect anomalies. These detected anomalies can be reported to a system user (see paragraph [0063]). Per paragraph [0064], the claimed invention is superior to prior art systems because it takes advantage of inter-feature correlation and predicts the value of one feature using values of other features and because it uses a threshold to predict anomalies.

Furthermore, the Appellants submit that the results of the method embodiments disclosed are also "tangible" and "concrete." Specifically, the claim limitations of "identifying anomalous events in said live system operations" and "reporting said anomalous events" are beneficial real-world results of performing the method of the invention (i.e., they are tangible and not abstract results, see Gottschalk v. Benson, 409 U.S. 63, 71-72, 175 USPQ 673,676 (1972)). That is, as system operations occur, the method is able to identify anomalous events that occur and to report out those events. The process steps are not abstract or theoretical. Additionally, the claim limitations of "identifying anomalous events in said live system operations" and "reporting said anomalous events" are substantially repeatable (i.e., concrete, see In re Swartz, 232 F.3d 862, 864, 56 USPQ2d 1703, 1704 (Fed. Cir. 2000). That is, as the live system operations proceed, the method will be able to identify and report out each anomalous event that occurs. The identification process is based on the previously calculated anomaly scores and previously established

> threshold. To ensure that the anomalous events will continue to be properly identified throughout the live system operations, the claim limitation of periodically recalculating the anomaly scores is also included.
> Therefore, independent claims 1 and 20 are directed to statutory subject matter under 35 U.S.C. §101. Further, dependent claims 2-7 and 21-26 are similarly patentable, not only by virtue of their dependency from a patentable independent claim, but also by virtue of the additional features of the invention they define. Moreover, the Appellants note that all claims are properly supported in the specification and accompanying drawings. In view of the foregoing, the Board is respectfully requested to reconsider and withdraw the rejections.

The "historical data" are merely unspecified variables. Applicant asserts that they represent things in the real world, but does not specify what that is. Therefore, the claims are not limited to a practical application. Therefore, the rejections stand.

## Argument 2

> (b) Appellants' Position Regarding The Rejection of Independent Claim 8
> In rejecting independent claim 8 under 35 U.S.C. § 101 for being directed to non- statutory subject matter, the Examiner indicated that In re Warmerdam, 33 F.3d 1354, 31 USPQ2d 1754 (Fed. Cir. 1994), which held that "...Taking several abstract ideas and manipulating them together adds nothing to the basic equation", was controlling.
> Specifically, the Examiner determined that the claimed invention did not have a useful, concrete and tangible result because the Appellant "manipulated a set of abstract 'history files' to solve purely algorithmic problems in the abstract". The Examiner further provided that "the fact that the invention is merely the manipulation of abstract ideas is clear. The data referred to by Applicant's idea of "history files" is simply an abstract construct that does not provide limitations in the claims to the transformation of real world data (such as monetary data or heart rhythm data) by some disclosed process. Consequently, the necessary conclusion under At&T, State Street and Warmerdam, is straight forward and clear. The claims take several abstract ideas (i.e., "history files" in the abstract) and manipulate them together adding nothing to the basic equation." The Appellants respectfully disagree.
> Independent claim 8 includes the claim limitations of "recording features of normal system operations in a history file" and "creating a model for each of said features of said normal system operations in said history file". These limitations imply that during normal system operations features of the system are determined in some manner. The features are then recorded (e.g., as historical data) in a history file. Then, for each

feature in the history file, a model is created. This aspect of the invention is explained in detail throughout the disclosure. For example, the Abstract provides that the system records actions performed as features in a history file and automatically creates a model for each feature. Paragraphs [0006] and [0023] provide that the invention begins with historical data maintained in a history file and that a model is created for each feature only from normal data in the history file. Paragraph [0020] references a dataset of N features from which N models are created. Therefore, the Appellants submit that contrary to the Examiner' s finding the "history files" are not just abstract ideas, but rather contain real world data (i.e., a recording of features of normal system operations) from which models are created (i.e., a model is created for each feature of normal system operations that is recorded).

Furthermore, if, as indicated by the Examiner, the data referred to by the "history files" is simply an abstract construct that did not provide limitations in the claims to the transformation of real world data by some disclosed process, it was still incumbent upon the Examiner to determine whether the method otherwise produces a useful, concrete or tangible result. That is, it is generally understood that to establish utility under 35 U.S.C. § 101 method inventions as a whole must produce a "useful, concrete and tangible result." (see State Street, 149 F.3d at 1373-74, 47 USPQ2d at 1601-02). Additionally, AT&T Corp v. Excel Communications, Inc. 172 F.3d 1352, 1358-59, 50 USPQ2d 1447, 1452 (Fed. Cir. 1999) provides that physical transformation "is not an invariable requirement, but merely one example, of how a mathematical algorithm [or law of nature] may bring about a useful application." If the Examiner determines that there is no physical transformation, additional review is required to determine if the claim provides a useful, tangible and concrete result. The review by the Examiner should focus not on each step, but one whether the final result achieved by the claimed invention is "useful, concrete and tangible" (see AT&T 172 F.3d at 1358-59).

The Appellants submit that the results of the method embodiments disclosed are "useful." Specifically, the Appellants submit that a credible, specific, and substantial use for the method of the invention (namely identifying and reporting anomalous events that occur during system operations) is readily apparent and well-established in the independent claims themselves. That is, claim 8 provides for a method of automatically identifying anomalous situations that occur during system operations. The limiting features in claim 8 include, but are not limited to, the following: (1) "recording features of normal system operations in a history file;" (2) "automatically creating a model for each of said features of said normal system operations in said history file;" (3) "calculating anomaly scores of said features of said normal system operations and storing said anomaly scores in a trained file;" (4) "establishing a threshold to evaluate whether events in live system operations are anomalies as compared to said normal system operations;" (5) "automatically identifying anomalous events in said live system operations based on said anomaly scores and on said threshold;" (6) "reporting said anomalous events;" (7) "periodically repeating said calculating"; and (8) "wherein said creating of said model for each of said features comprises: establishing relationships that exist between each of said features for said normal system operations; selecting a labeled feature from said features; mathematically rearranging said relationships

from the point of view of said labeled feature to create a solution for said labeled feature, wherein said solution comprises a model for said labeled feature; selecting different features as said labeled feature and repeating said process of mathematically rearranging said relationships to produce solutions from the point of view of each remaining feature as models for the remaining features." Those skilled in the art would immediately appreciate why the invention is useful (i.e., would appreciate why it is important to be able to identify when anomalous events occur during system operations and to report out the occurrence of those anomalous events).

This credible, specific, and substantial use for the method of the invention (namely identifying and reporting anomalous events that occur during live system operations) is further asserted in the disclosure at paragraph [0004]. That is, in order to achieve a goal of autonomic computing it is important that a target system be able to perform self-diagnosis. Per paragraph [0018], the claimed invention provides a general solution to conventional problems associated with self-diagnosis by providing a method that uses an additive approach to combine evidence from multiple sources (i.e., history files) and then uses a probabilitstic thresholding approach to detect anomalies. These detected anomalies can be reported to a system user (see paragraph [0063]). Per paragraph [0064], the claimed invention is superior to prior art systems because it takes advantage of inter-feature correlation and predicts the value of one feature using values of other features and because it uses a threshold to predict anomalies.

Furthermore, the Appellants submit that the results of the method embodiments disclosed are also "tangible" and "concrete." Specifically, the claim limitations of "identifying anomalous events in said live system operations" and "reporting said anomalous events" are beneficial real-world results of performing the method of the invention (i.e., they are tangible and not abstract results, see Gottschalk v. Benson, 409 U.S. 63, 71-72, 175 USPQ 673,676 (1972)). That is, as system operations occur, the method is able to identify anomalous events that occur and to report out those events. These process steps are not abstract or theoretical. Additionally, the claim limitations of "identifying anomalous events in said live system operations" and "reporting said anomalous events" are substantially repeatable (i.e., concrete, see In re Swartz, 232 F.3d 862, 864, 56 USPQ2d 1703, 1704 (Fed. Cir. 2000). That is, as the live system operations proceed, the method will be able to identify and report out each anomalous event that occurs. The identification process is based on the previously calculated anomaly scores and previously established threshold. To ensure that the anomalous events will continue to be properly identified throughout the live system operations, the claim limitation of periodically recalculating the anomaly scores is also included.

Therefore, independent claim 8 is directed to statutory subject matter under 35 U.S.C. § 101. Further, dependent claims 9-14 are similarly patentable, not only by virtue of their dependency from a patentable independent claim, but also by virtue of the additional features of the invention they define. Moreover, the Appellants note that all claims are properly supported in the specification and accompanying drawings. In view of the foregoing, the Examiner is respectfully requested to

reconsider and withdraw the rejections.

The "historical data" and the calculated "anomalies" are merely unspecified variables. Applicant asserts that they represent things in the real world, but does not specify what that is. Therefore, the claims are not limited to a practical application. Therefore, the rejections stand.

## Argument 3

(c) Appellants' Position Regarding The Rejection of Independent Claim 14

In rejecting independent claim 14 under 35 U.S.C. § 101 for being directed to non- statutory subject matter, the Examiner indicated that In re Warmerdam, 33 F.3d 1354, 31 USPQ2d 1754 (Fed. Cir. 1994), which held that "...Taking several abstract ideas and manipulating them together adds nothing to the basic equation", was controlling. Specifically, the Examiner determined that the claimed invention did not have a useful, concrete and tangible result because the Appellant "manipulated a set of abstract 'history files' to solve purely algorithmic problems in the abstract". **The Examiner further provided that "the fact that the invention is merely the manipulation of abstract ideas is clear. The data referred to by Applicant's idea of "history files" is simply an abstract construct that does not provide limitations in the claims to the transformation of real world data (such as monetary data or heart rhythm data) by some disclosed process.**

Consequently, the necessary conclusion under AT&T, State Street and Warmerdam, is straight forward and clear. The claims take several abstract ideas (i.e., "history files" in the abstract) and manipulate them together adding nothing to the basic equation." The Appellants respectfully disagree.

Independent claim 14 includes the claim limitations of "**recording features of normal system operations in a history file"** and "creating a model for each of said features of said normal system operations in said history file". These limitations imply that during normal system operations features of the system are determined in some manner. The features are then recorded (e.g., as historical data) in a history file. Then, for each feature in the history file, a model is created. This aspect of the invention is explained in detail throughout the disclosure. For example, the Abstract provides that the system records actions performed as features in a history file and automatically creates a model for each feature. Paragraphs [0006] and [0023] provide that the invention begins with historical data maintained in a history file and that a model is

created for each feature only from normal data in the history file. Paragraph [0020] references a dataset of N features from which N models are created. Therefore, the Appellants submit that contrary to the Examiner' s finding the "history files" are not just abstract ideas, but rather contain real world data (i.e., a recording of features of normal system operations) from which models are created (i.e., a model is created for each feature of normal system operations that is recorded). Furthermore, if, as indicated by the Examiner, the data referred to by the "history files" is simply an abstract construct that did not provide limitations in the claims to the transformation of real world data by some disclosed process, it was still incumbent upon the Examiner to determine whether the method otherwise produces a useful, concrete or tangible result. That is, it is generally understood that to establish utility under 35 U.S.C. § 101 method inventions as a whole must produce a "useful, concrete and tangible result." (see State Street, 149 F.3d at 1373-74, 47 USPQ2d at 1601-02). Additionally, AT&T Corp v. Excel Communications, Inc. 172 F.3d 1352, 1358-59, 50 USPQ2d 1447, 1452 (Fed. Cir. 1999) provides that physical transformation "is not an invariable requirement, but merely one example, of how a mathematical algorithm [or law of nature] may bring about a useful application." If the Examiner determines that there is no physical transformation, additional review is required to determine if the claim provides a useful, tangible and concrete result. The review by the Examiner should focus not on each step, but on whether the final result achieved by the claimed invention is "useful, concrete and tangible" (see AT&T 172 F.3d at 1358-59).
The Appellants submit that the results of the method embodiments disclosed are "useful." Specifically, the Appellants submit that a credible, specific, and substantial use for the method of the invention (namely identifying and reporting anomalous events that occur during system operations) is readily apparent and well-established in the independent claims themselves. That is, each of the independent claims provides for a method of automatically identifying anomalous situations that occur during system operations. The claim limitations in claim 14 include, but are not limited to, the following: (1) "recording features of normal system operations in a history file;" (2) "automatically creating a model for each of said features of said normal system operations in said history file;" (3) "calculating anomaly scores of said features of said normal system operations and storing said anomaly scores in a trained file;" (4) "establishing a threshold to evaluate whether events in live system operations are anomalies as compared to said normal system operations;" (5) "automatically identifying anomalous events in said live system operations based on said anomaly scores and on said threshold;" (6)"reporting said anomalous events;" (7)"periodically repeating said calculating"; and (8) "wherein said calculating comprises: predicting a likelihood that each feature will be normal when one or more of the other features are abnormal, using said model of each of said features; repeating said predicting using different presumptions about other features being normal and abnormal to produce said trained file of a plurality of anomaly scores for each of said features." Those skilled in the art would immediately appreciate why the invention is useful (i.e., would appreciate why it is important to be able to identify when anomalous events occur during system operations and to report out the occurrence of those anomalous events).

> This credible, specific, and substantial use for the method of the invention (namely identifying and reporting anomalous events that occur during live system operations) is further asserted in the disclosure at paragraph [0004]. That is, in order to achieve a goal of autonomic computing it is important that a target system be able to perform self-diagnosis. Per paragraph [0018], the claimed invention provides a general solution to conventional problems associated with self-diagnosis by providing a method that uses an additive approach to combine evidence from multiple sources (i.e., history files) and then uses a probabilitstic thresholding approach to detect anomalies. These detected anomalies can be reported to a system user (see paragraph [0063]). Per paragraph [0064], the claimed invention is superior to prior art systems because it takes advantage of inter-feature correlation and predicts the value of one feature using values of other features and because it uses a threshold to predict anomalies.
>
> Furthermore, the Appellants submit that the results of the method embodiments disclosed are also "tangible" and "concrete." Specifically, the claim limitations of "identifying anomalous events in said live system operations" and "reporting said anomalous events" are beneficial real-world results of performing the method of the invention (i.e., they are tangible and not abstract results, see Gottschalk v. Benson, 409 U.S. 63, 71-72, 175 USPQ 673,676 (1972)). That is, as system operations occur, the method is able to identify anomalous events that occur and to report out those events. These claim limitations are neither abstract nor theoretical. Additionally, the claim limitations of "identifying anomalous events in said live system operations" and "reporting said anomalous events" are substantially repeatable (i.e., concrete, see In re Swartz, 232 F.3d 862, 864, 56 USPQ2d 1703, 1704 (Fed. Cir. 2000). That is, as the live system operations proceed, the method will be able to identify and report out each anomalous event that occurs. The identification process is based on the previously calculated anomaly scores and previously established threshold. To ensure that the anomalous events will continue to be properly identified throughout the live system operations, the claim limitation of periodically recalculating the anomaly scores is also included.
>
> Therefore, independent claim 14 is directed to statutory subject matter under 35 U.S.C. § 101. Further, dependent claims 15-19 are similarly patentable, not only by virtue of their dependency from a patentable independent claim, but also by virtue of the additional features of the invention they define. Moreover, the Appellants note that all claims are properly supported in the specification and accompanying drawings. In view of the foregoing, the Examiner is respectfully requested to reconsider and withdraw the rejections.

The "system" need not be a real world "system" in the claims. It can be a pure simulation with no practical application in the real world.

Likewise, the "historical data" and the calculated "anomalies" are merely unspecified variables. Applicant asserts that they represent things in the real world, but does not specify what that is. Therefore, the claims are not limited to a practical application. Therefore, the rejections stand.

## **Argument 4**

B. The 35 U.S.C §112 Rejection Claims 1-26

1. The Position in the Office Action
The position of the Examiner, as set out in paragraphs 1-14 of the Office Action dated April 17, 2007 is quoted below.
Claims 1-26 are rejected under 35 U.S.C. § 112, first paragraph because the current case law (and accordingly, the MPEP) require such a rejection if a § 101 rejection is given because when Applicant has not in fact disclosed the practical application for the invention, as a matter of law there is no way Applicant could have disclosed how to practice the undisclosed practically application.

2. The Appellants' Position Regarding Claims 1, 8, 14, and 20 under 35 U.S.C. 8112
Given the Appellants position that claims 1-26 are directed to statutory subject matter under 35 U.S.C. § 101 (see above discussion in section VII A.2) and further given the fact that the only basis for the rejection of claims 1-26 under 35 U.S.C. § 112 is the existence of the rejection of those claims under 35 U.S.C § 101 rejections, the Board is respectfully requested to reconsider and withdraw the rejections.

Applicant has not disclosed the practical application, much less how to practice the unspecified practical application. Therefore, the rejections stand.

## ***Conclusion***

The prior art made of record and not relied upon is considered pertinent to Applicant's disclosure. Specifically:

A. Chalasani et al. (U.S. Patent Number 7,055,052 B2; dated 30 MAY 2006; class 714; subclass 004) discloses a self healing grid architecture for decentralized component-based systems.

B. Hayo et al. (U.S. Patent Number 7,027,962 B2; dated 11 APR 2006; class 702; subclass 197) discloses a system and method for self-configuring and self-optimizing filters.

C. Mandal (U.S. Patent Number 6,959,264 B2; dated 25 OCT 2005; class 702; subclass 186) discloses an autonomous computing probe agent.

Any inquiry concerning this communication or earlier communications from the Examiner should be directed to Wilbert L. Starks, Jr. whose telephone number is (571) 272-3691.

Alternatively, inquiries may be directed to the following:

| | |
|---|---|
| **S. P. E. David Vincent** | **(571) 272-3080** |
| **Official (FAX)** | **(571) 273-8300** |

Wilbert L. Starks, Jr.
Primary Examiner
Art Unit 2129

WLS

04 SEP 2007

9/4/07
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